Breast Mass Detection in Mammography Images based on Improved Deep Transformed Model

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1 Introduction

Breast cancer is a widespread type of cancer that originates in the cells of the breast, affecting both men and women, with a higher prevalence in women. Over time, breast cancer can infiltrate nearby healthy tissues and potentially spread to other parts of the body, including the lymph nodes. Recognized as a significant global health concern, breast cancer disproportionately affects women. The development of breast cancer is often linked to abnormal cell growth in the breast, leading to the formation of a lump or tumour. Mammograms, utilizing breast X-ray scans, play a crucial role in diagnosing breast cancer. Early identification through mammography is vital for optimal treatment outcomes and improved survival rates. Failure to detect breast cancer early increases the likelihood of it spreading to other areas, posing greater challenges for treatment.

However, interpreting mammography images can be complex due to overlapping tissue, creating difficulties in distinguishing between normal tissue and potential abnormalities such as lumps. Addressing this complexity is crucial for locating breast abnormalities accurately in mammograms. Successful breast cancer treatment heavily relies on early detection, emphasizing the need for advancements in imaging techniques to enhance accuracy and enable timely intervention.

The primary screening technique for breast cancer is mammography, and reducing the disease's fatality rate depends on early diagnosis. Despite its importance, interpreting mammograms can be challenging, with experienced radiologists sometimes missing minor abnormalities. Deep learning models have the potential to distinguish between benign and malignant lesions and identify features of anomalies like breast lumps. By using deep learning models to segment breast masses, radiologists can simplify the visualization and characterization of masses. Early detection is paramount for improving mortality rates, with mammography being the primary screening tool.

Deep learning has the potential to enhance the accuracy of breast cancer detection and segmentation in mammography images. These models can be trained to learn the features of breast masses, distinguish between benign and malignant lesions, and accurately segment breast masses.

The proposed Deep MammoSegNet is inspired by [1], where a You Only Look Once (YOLO) is used for Region of Interest (ROI) and Local – Global (LOGO) is used for breast mass segmentation. But the authors used the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) dataset for both training and testing, with the INBreast dataset serving as an additional test set. However, their model performed better on the CBIS-DDSM dataset than the INBreast dataset, highlighting a limitation. The proposed breast mass detection consists of three modules: pre-processing, extraction of ROI and Mass segmentation.

The object detection model for detecting malignant lesions uses the YOLOv8 architecture, which expands upon earlier iterations of the well-liked YOLO family. YOLOv8 leverages a host of advances to boost speed and accuracy including a new backbone network, anchor-free detection, and enhanced data augmentations. To allow robust performance even when lesions represent a minor fraction of the total mammography scan, we additionally employ targeted augmentations such as mosaic augmentations and grid masking.

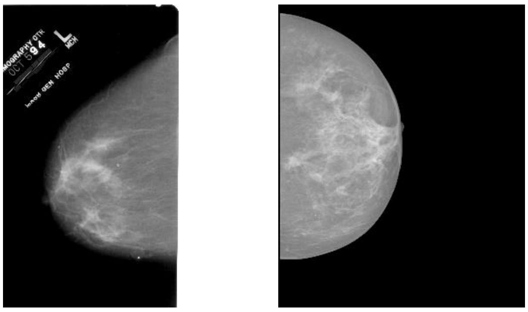
Sect. 2 of the article elaborates on the literature survey and related works of the proposed work. The proposed system is discussed in Sect. 3.

The following are the primary contributions of this proposed work:

1. A lightweight architecture to perform accurate mass detection with less computational time. The architecture consists of two modules (1) the backbone module for extraction of ROI from breast masses and (2) the segmentation module.

2. The Deep MammoSegNet is evaluated on both CBIS-DDSM and INBreast dataset and the supremacy of the model is studied.

3. The proposed detector detects breast masses with high inference speed and good accuracy.



(a) (b)

Figure 1. Sample Mammography Image

(a): from CBIS-DDSM dataset.

(b): from INBreast dataset.

2 Related Works

In this segment, we provide an overview of a few related studies on deep learning techniques for the detection and segmentation of breast cancer. Lydia Bouzar-Benlabiod *et al* [2], introduced a novel breast cancer detection architecture based on a Convolutional Neural Network - Case-Based Reasoning (CNN-CBR) system for mammogram classification, utilizing the publicly available CBIS-DDSM dataset. This proposed architecture obtains less accurate than certain cutting-edge deep learning techniques, the suggested system demonstrated comparability with current techniques, with an accuracy of 86.71% in classifying mammograms as normal, benign, or malignant. This architecture combines a CBR system for classification with a CNN for feature extraction, providing explainability in decision-making and the capacity to use historical instances to enhance performance on small datasets.

Jihen Frikha Elleuch *et al* [3], introduced a method that blends possibility theory with a clustering paradigm was used to explore breast cancer anomaly detection. This method makes use of possibility theory to make decisions and to pick and classify features. The texture analysis tools like local binary patterns are necessary for feature extraction, clustering helps to alleviate any sparsity difficulties. This method produces encouraging results, outperforming current techniques on the CBIS-DDSM dataset with classification accuracy of 99.4% for micro-calcification detection and 95.4% for bulk detection. Even with certain drawbacks, such as unused possibility features, the method has a great deal of promise to improve the accuracy of cancer detection.

Hamed Pezeshki [4], proposed a method that addresses the segmentation of breast tumours in digital mammography by precisely defining the mass core and spiky areas. This method uses fuzzy C-means clustering, which is well-known for handling hazy borders, to provide amazing outcomes. As measured against the ground truth data from the Digital Database for Screening Mammography (DDSM), a popular dataset that includes more than 2600 patient scans with various anomalies, the method obtains great accuracy, as evidenced by its Dice value of 0.9557 and Jaccard coefficient of 0.9132. This encouraging result outperforms existing segmentation methods and opens the door to more accurate tumour identification and treatment planning.

Ghada Hamed Aly *et al* [5], presented a YOLO-v3 based breast mass detection and classification method, achieving high accuracy in both tasks. For testing and learning transfer, the method uses the INBreast dataset as well as extra mammograms from General Electric and Hologic scanners. For mass detection and classification, the YOLO-v3 architecture is utilized, along with preprocessing methods like data augmentation and normalization to enhance the generalizability of the model. K-means clustering is used to create custom anchor boxes appropriate for breast mass detection, and the classification performance of various architectures, including Residual Neural Network (ResNet) and Inception, is compared. This system attains classification accuracy of 84.6%, average precision for mass detection of 94.2%, and mass detection accuracy of 89.4%.

Asma Baccouche *et al* [6], developed YOLO-based model to detect breast cancer in its early stages in mammography, even in cases where the initial diagnosis was normal. This system obtained outstanding early detection accuracy of 88% for mass lesions, 95% for architectural deformation, and 92% overall by utilizing image-to-image translation and YOLO approaches. However, calcification identification is still an issue. The National Institute of Cancerology (INCAN) dataset's worrisome findings from earlier mammograms were very well-predicted by the model, and this prediction was later verified in additional screenings, indicating the model's potential for early intervention.

Steven J. Frank [7], proposed a deep learning architecture that effectively highlights possible breast masses in mammograms by integrating object detection and CNN. This method employs a two-stage process: a CNN analyses subregions within the ROI to improve mass detection, after an object-detection algorithm has identified the ROIs with high precision. With identified ROIs occupying less than 20% of the tissue on average, this strategy minimizes needless review time while effectively drawing attention to worrisome spots. This work shows its potential to increase mammography review efficiency and accuracy for early cancer diagnosis by validating its efficacy on a variety of datasets, such as CBIS-DDSM and INBreast.

Fei Yan *et al* [8], presented an automated mammography-based breast cancer diagnosis system using a combination of area extraction, pectoral muscle removal, picture segmentation, and feature weighting. This system's output is an ensemble classifier that outperforms previous methods with an average accuracy of 93.26% on the DDSM dataset and 91.00% on the Mammographic Image Analysis Society (MIAS) dataset. Even though there are still difficulties in getting hold of big datasets and improving feature extraction, this research has a lot of promise.

Khaoula Belhaj Soulami *et al* [9], introduced a novel capsule network (CapsNet) architecture for precise classification of suspicious regions in digital mammograms. CapsNet combines preprocessing, wavelet and curvelet feature extraction, and a convolutional neural network for classification. This architecture yields remarkable results, with respective Area Under Curve (AUC) of 0.997 and 0.9 for binary classification (normal vs. abnormal) and 77.78% for multi-class classification (normal, benign, and malignant). Notably, this effective architecture of CapsNet beats prior methods in spotting suspicious breast masses and works exceptionally well in training on low-cost Graphics Processing Unit (GPU). This study makes use of the advantages of a hybrid dataset, which consists of normal cases from both the INBreast and DDSM databases in addition to aberrant cases selected from the latter.

Volkan Müjdat Tiryaki *et al* [10], introduced a cascaded Deep Transfer Learning (DTL) approach for accurate analysis of film mammograms. This method makes use of Visual Geometry Group 16 (VGG16) for promising mass classification and U-net++Xception for accurate mass segmentation, attaining an astounding 98.91% accuracy. The segmentation process in this approach still has some small false positives and negatives, but overall performance is promising. The dataset from the Breast Cancer Digital Repository (BCDR) is used in the study, providing a solid basis for future research.

Subasish Mohapatra *et al* [11], evaluated VGG16, ResNet50, and DenseNet121 for breast cancer detection on histopathological images, achieving high accuracy with VGG16 at 92.3%, ResNet50 at 93.5%, and DenseNet121 at 94.1%. To avoid overfitting, their typical deep learning workflow involves preprocessing, feature extraction, and classification along with image resizing, normalization, and augmentation. This models show promise for automating parts of the diagnosis process for breast cancer, which could increase screening effectiveness, result in early intervention, and enhance patient outcomes.

Deepti Sharma *et al* [12],worked with machine learning techniques like support vector machines and logistic regression to develop a flexible framework for early breast cancer prediction. This framework outperforms current studies with an astounding 97.14% accuracy on the Wisconsin Breast Cancer Dataset (WBCD). Its versatility comes from its capacity to target different diseases and integrate a variety of classifiers.

Jung Hyun Yoon *et al* [13], conducted a study using a large dataset of 108,079 screening mammograms from three independent institutions to evaluate an Artificial Intelligence-Computer-Assisted Detection/Diagnosis (AI-CAD) system's outcomes in the mammographic interpretation workflow. The AI-CAD approach increased specificity by lowering false positives by 9.1% and found an extra 17.9% of tumours that radiologists had overlooked during initial screening. There was a trade-off, too, as its greater recall rate resulted in more flagged discoveries and subsequently biopsies. This study used a two-phase method in which radiologists independently analysed mammograms at first, and then they re-evaluated the same mammograms with the indicated markings from the AI-CAD system superimposed.

Qing Lin *et al* [14], proposed the method of deep learning to tackle breast cancer diagnosis through mammography microcalcification analysis. Leveraging Faster Region-Based Convolutional Neural Network (RCNN) for automated detection and classification, the AI system scans mammograms, pinpointing potential calcifications and categorizing them as benign or malignant. This method promises increased diagnosis efficiency and accuracy, but more research is necessary due to the need for high-quality data and certain algorithmic biases.

Tingting Liao *et al* [15], presented a study using a DenseNet CNN to classify benign and malignant asymmetric lesions in mammograms, achieving an k of 0.778, significantly outperforming two junior radiologists. This two-stage method makes use of DenseNet's enhanced feature extraction capabilities and entails asymmetric focus detection and benign-malignant categorization. Because it can identify questionable areas and provide preliminary classifications, DenseNet CNN outperforms junior radiologists in accuracy and offers radiologists the possibility of early detection and less effort.

Yash Amethiya *et al* [16], proposed a method for breast cancer detection using a diverse arsenal of machine learning algorithms like K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM) and biosensor data. This study compares different models through analysis of blood samples and the WBCD dataset. Some models achieve remarkable accuracy, such as 98.54% for a weighted Naive Bayes approach and 96.49% for a neural network. Although there are still issues with computing cost and model development, the potential is clear.

Xiang Yu *et al* [17], proposed a multiple-level thresholding approach for breast mass detection, involving preprocessing steps such as pectoral muscle removal and contrast enhancement. Using multiple-level thresholding, this method first uses coarse segmentation of breast mass candidates. This method then uses fine segmentation on big connected components and patch classification using Deep CNNs such as ResNet50. This method is effective in terms of calculation, can handle a range of breast densities, and has a high sensitivity of 87% for CBIS-DDSM at 2.86 False Positive Index (FPI) and 96% for INBreast at 1.29 FPI.

Bita Asadi *et al* [18], presented an efficient breast cancer detection method using a cascade deep learning network with two stages: segmentation using UNet architecture and classification using the ResNet50 model. This make use of a dataset of 2780 mammography pictures from ImageNet that has been pre-processed using histogram equalization and has a 90/10 train/test split. While ResNet50 gathers characteristics and categorizes tumours as benign or malignant, UNet uses semantic segmentation to isolate tumour areas. With an F1 score of 98.41%, the classification accuracy reaches 98.61%, while the segmentation model obtains an F1 score of 97.3%. Tumour detection and classification are enhanced by the cascade design, wherein ResNet50 extracts discriminative features for accurate benign/malignant classification and UNet provides precise segmentation masks for the classification stage.

3 Proposed System

3.1 Dataset Description

The DDSM has been modified and standardized as CBIS-DDSM dataset. Both the CBIS-DDSM [19] [20] [21] and INBreast [1] are FFDM (Full Field Digital Mammography) Mammograms. INBreast dataset, comprises of 115 cases (410 images) in total, of which 25 are from patients who had Mastectomy (two images per case) and 90 are from women whose breasts have been affected (four images per case).

Table.1 shows the dataset description of both the CBIS-DDSM and INBreast dataset.

Title	CBIS-DDSM Dataset	INBreast Dataset
No. of Images	10239	410
No. of Participants	1556	115
Total No. of Malignant Cases	6100	152
Total No. of Benign Cases	4139	258

3.2 Data Pre-processing

The first step is the data pre-processing. Both the CBIS-DDSM and INBreast dataset contains the images in Digital Imaging and Communications in Medicine (DICOM) format. Our first aim is to convert these DICOM images into Portable Network Graphics (PNG). The DICOM images are in .dcm format. For this we are using a DICOM converter for conversion. The images in the CBIS-DDSM dataset contains some medical signs in it. The image undergoes four pre-processing steps such as binarizing and thresholding, adaptive cropping, adaptive padding and Contrast Limited Adaptive Histogram Equalization (CLAHE). The pre-processed images are used as input in both the detection of ROI in breast image and mass segmentation.

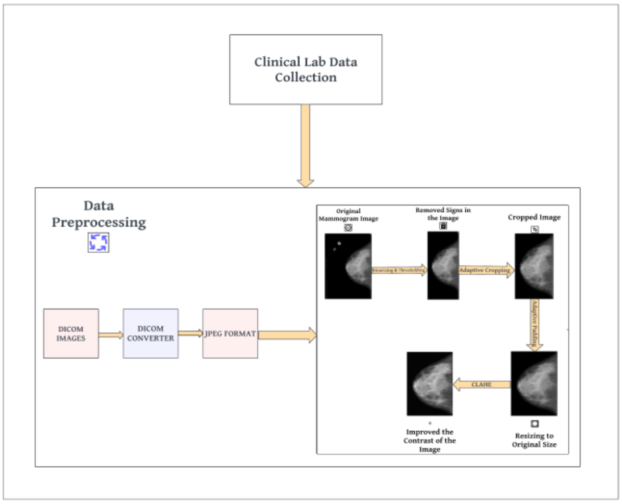


Figure 2. Block Diagram of Pre-processing Module

3.2.1 Binarizing and Thresholding

Binarizing and Thresholding plays an important role in detection which is used to select areas of interest of an image, while ignoring the parts we are not concerned with. Binarizing and Thresholding is mathematically represented as follows:

$$\mathrm{bin}_{\mathrm{img}}[x,y] = \begin{cases} 1 \; if \; I(x,y) \geq T \\ 0 \; if \; I(x,y) < T \end{cases} \qquad (1)$$

where:
x – row pixel of an image
y – column pixel of an image
T – threshold value
I – pixel value
binimg – binarized image
img – input image

Binarizing helps in separating dark, high-contrast medical signs from the lighter background. Then, by using an approximate thresholding value we can remove the medical signs from the mammography images.

3.2.2 Adaptive Cropping

Adaptive Cropping is the method of improving an image by removing unnecessary parts. The size of cropping depends on the height and width of the image. The adaptive cropping can be mathematically represented as follows:

$$crop_{img}[x,y] = (y + crop\_h : y + h - crop\_h , x + crop\_w : x + w - crop\_w) \quad (2)$$

where:
x – row pixel of an image
y – column pixel of an image
h, w – original image height and width
crop_h , crop_w – calculated crop sizes based on the specified percentage

3.2.3 Adaptive Padding

Adaptive padding is the method to scale the cropped image to the original image size.

3.2.4 CLAHE

CLAHE is useful in improving the image contrast which is helpful in detection. The CLAHE can be mathematically represented as follows:

$$\mathrm{CLAHE}(x, y) = \mathrm{clip}\left(\frac{\sum_{m=0}^{I(x,y)} \sum_{i=0}^{N_x} \sum_{j=0}^{N_y} \mathrm{histogram}(I_{tile}(i,j),m)}{\mathrm{clip}(C_{max},1,\infty)}, 0,1\right) \times L \quad (3)$$

where:
x – row pixel of an image
y – column pixel of an image
$I_{tile}(i, j)$ – pixel value at coordinates (i, j) within a tile.
C_{max} – contrast limit.
clip (a, min, max): Restricts the value of a to be within the specified range
L: maximum pixel intensity value.

Algorithm 1: Pre-processing stage

1. **Input** Image (img)
2. **Get** image height and width (h, w)
3. **Initialize** T value
4. **Calculate** binarizing and thresholding
5. **IF** $I(x,y) \geq T$ **THEN**
6. $\quad bin_{img}[x, y] = 1$
7. **ELSE**
8. $\quad bin_{img}[x, y] = 0$
9. **ENDIF**
10. **Initialize** crop_h, crop_w value
11. **Calculate** adaptive cropping value
12. $crop_{img}[x,y] = (y + crop\_h : y + h - crop\_h , x + crop\_w : x + w - crop\_w)$
13. **Initialize** L value
14. **Calculate** CLAHE
15. $\mathrm{CLAHE}(x, y) = \mathrm{clip}\left(\frac{\sum_{m=0}^{I(x,y)} \sum_{i=0}^{N_x} \sum_{j=0}^{N_y} \mathrm{histogram}(I_{tile}(i,j),m)}{\mathrm{clip}(C_{max},1,\infty)}, 0,1\right) \times L$
16. **Output** Pre-processed image

3.3 Detection of Region of Interest in Breast Masses

The second stage is to determine the ROI in breast masses. At this point, multi-object detection tasks are not required. We just need to locate the breast lump. Thus, for this targeted detection task, we use Deep MammoSegNet model. The Deep MammoSegNet model contains the most recent version of the well-liked YOLO object detection architecture, known as YOLOv8, builds on earlier iterations to increase speed and accuracy. Important improvements such as data augmentation and the Mean Squared Error (MSE) loss function for small object detection allow this model to reach cutting edge results on benchmarks while preserving high frames per second. Because of these features, YOLOv8 is a good choice for breast mass detection since it only needs a real-time, accurate detector that is dedicated to locating masses; it does not require more comprehensive multi-object detection. As the crucial step before segmentation, we can consistently identify breast mass ROIs by implementing the Deep MammoSegNet model and taking use of its accurate detection capabilities.

Algorithm 2: Detection of ROI

1. **Input** Image (pre_processed_image,roi_image)
2. **Get** label (roi_image)
3. label_image = label (roi_image)
4. **Calculate** non zero coordinates of label_image
5. **Calculate** bounding box coordinates
6. xmin = bbox[1].min()
7. ymin = bbox[0].min()
8. xmax = bbox[1].max()
9. ymax = bbox[0].max()
10. **Generate** plot
11. pre_processed_image = plot((xmin, ymin), xmax - xmin, ymax – ymin)
12. mammo_image = pre_processed_image
13. **Output** mammo_image

3.4 Mass Segmentation

Image segmentation is a crucial step in breast mass detection from the mammograms in datasets like CBIS-DDSM and INBreast. The goal of segmentation remains accurately delineating the boundaries of suspicious breast masses from the surrounding breast tissue, enabling further analysis of the mass. With these public benchmark datasets providing expert-annotated images, deep learning segmentation can be trained to reliably extract breast mass regions. Additional techniques like attention mechanisms may improve focus on desired mass areas in these diverse training sets. Evaluation metrics can quantify model accuracy against ground truth masks. The resulting model can then be used to automate identification of malignant areas from new mammogram images. The output segmentation highlights breast tumour locations to assist radiologists in diagnoses. Key aspects that impact performance include architectural modifications to handle varying mass shape/textures and data augmentation strategies like rotations/translations to expand limited training data. Reliable breast mass segmentation is thus an essential preprocessing step for computer-aided diagnosis from these benchmark mammogram datasets towards real-world breast cancer diagnosis support.

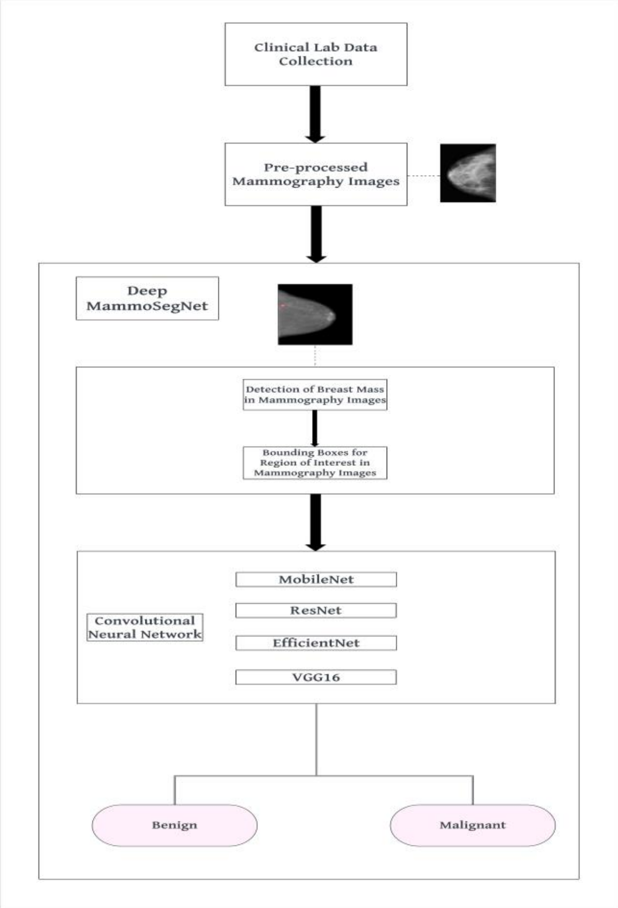


Figure 3. Proposed System Diagram of the Deep MammoSegNet model

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